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14. ABSTRACT

Electric motor and power electronics based inverter are the major components in industrial and automotive electric drives. In this paper we present a fault diagnostics system developed using machine learning technology for detecting and locating multiple classes of faults in an electric drive. A machine learning algorithm has been developed to automatically select a set of representative operating points in the (torque, speed) domain, which in turn is sent to the simulated electric drive model to generate signals for the training of a diagnostic neural network, "Fault Diagnostic Neural Network" (FDNN). We presented our study on two different neural network systems and show that a well-designed hierarchical neural network system is robust in detecting and locating faults in electric drives.

15. SUBJECT TERMS

Keywords: – intelligent systems, neural networks, machine learning.

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Fault Diagnostics in Electric Drives Using Machine Learning

Yi L. Murphey, *Senior Member, IEEE,* M. Abul Masrur, *Senior Member, IEEE,* ZhiHang Chen

Abstract. Electric motor and power electronics based inverter are the major components in industrial and automotive electric drives. In this paper we present a fault diagnostics system developed using machine learning technology for detecting and locating multiple classes of faults in an electric drive. A machine learning algorithm has been developed to automatically select a set of representative operating points in the (torque, speed) domain, which in turn is sent to the simulated electric drive model to generate signals for the training of a diagnostic neural network, "Fault Diagnostic Neural Network" (FDNN). We presented our study on two different neural network systems and show that a well-designed hierarchical neural network system is robust in detecting and locating faults in electric drives.

***Keywords* – intelligent systems, neural networks, machine learning.**

1. Introduction

Fault diagnostics for internal combustion (IC) engine vehicles has been well investigated [1,4,10], but not to the same extent for electric or hybrid vehicles. However, there are active researches in electrical system diagnostics [2, 5, 6, 8, 9]. Rule-based expert systems and decision trees are the two traditional diagnostic techniques, but they have serious limitations. A rule-based system often has difficulties in dealing with novel faults and acquiring complete knowledge to build a reliable rule-base, and is system dependent. A decision tree can be very large for a complex system, and it is also system dependent such that even small engineering changes can mean significant updates [2]. More recently model based approaches, fuzzy logic, artificial neural networks (ANN), case based reasoning (CBR) are popular techniques used in various fault diagnostics problems in electrical systems.

Our research is one step more advanced from those published works. Most of the existing diagnostic systems are built to detect a faulty condition against the normal condition. We present an advanced machine learning technology for the development of a robust diagnostic system that has the capability of detecting and locating multiple classes of faults in an electric drive operating at any valid (torque, speed) conditions. The diagnostic system FDNN(Fault Diagnostic Neural Network) is trained with simulation data generated by a robust machine learning algorithm. The diagnostic results provided by FDNN can be used to make a gracefully degradable [6, 8] operation of a faulty drive possible. Experiments were conducted both on the simulated data and the results show that the proposed diagnostic system is very effective in detecting multiple classes of faulty conditions of an inverter in an electric drive operating at any valid (torque, speed) point.

2. Electric Drive Fault Detection Using Signal Analysis and Machine Learning

Figure 1 illustrates our approach to fault diagnostics of an electric drive. "SIM_drive", a simulation model of a field oriented control electric drive with a power electronics based inverter and a 3-phase induction motor(see Figure 2), is developed and implemented using the Matlab-Simulink software. SIM_drive has the capability of simulating normal operation condition of an electric drive as well as the faulty conditions of the open and post-short-circuit faults in an inverter switch. The SIM_drive model operates at any selected (torque, speed) operating point under normal and various faulty conditions. Since in real world an electric drive can operate at different (torque, speed) points, a diagnostic system should be trained to be robust throughout the (torque, speed) domain.

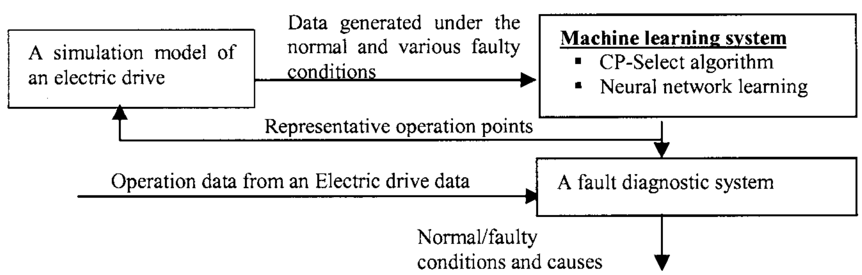


Figure 1. Illustration of a model based fault diagnostic system driven by machine learning.

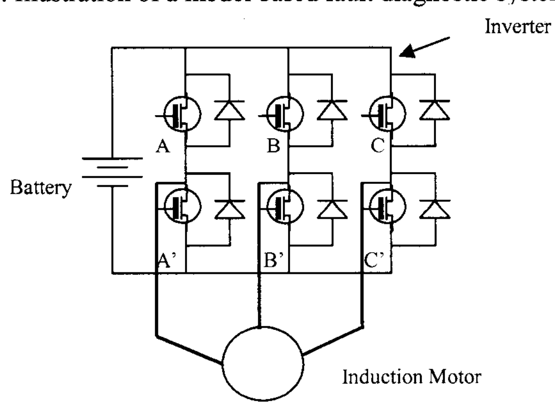


Figure 2. A a six-switch inverter in a 3-phase electric drive.

A machine learning algorithm is developed to select representative operating points from the (torque, speed) domain for use by the SIM_drive model to generate training data. The detail of the SIM_drive can be found in [7]. In this paper we focus on the machine learning system and the fault diagnostic system.

The objective of the machine learning approach is to train a diagnostic system on the representative data so it has the capability of performing accurate fault diagnostics in an electric drive that operates at any valid operating point. The intelligent system used in this research is a multi-class neural network system.

2.1 Multiple class fault detection

We are attempting to develop a robust diagnostic system to detect the faulty cases in the electric drive system shown in Figure 2. The challenges in developing such robust diagnostic systems lie in the fact that it is easier to identify signatures of a faulty condition against the normal condition, whereas signal signatures of one fault against another one are often quite subtle. We model the fault diagnostics in electric drive as a multi-class classification problem.

Figure 3 illustrates the computational steps involved in the signal fault detection system, where the input consists of the input voltages V_{an}, V_{bn}, V_{cn} to the motor, the currents I_a, I_b, I_c, and the motor electro-magnetic torque T_e. The first computational step is to segment the signals and extract the signal features from each segment. The signal segments are then analyzed by an artificial neural network, which is trained on the signals generated by SIM_drive at the parameter points selected by the CP-Select algorithm, a machine learning algorithm. The major research contribution in this paper is the machine learning technology used to train a neural network that can robustly detect and locate faults inside an electric drive operated under any given valid condition.

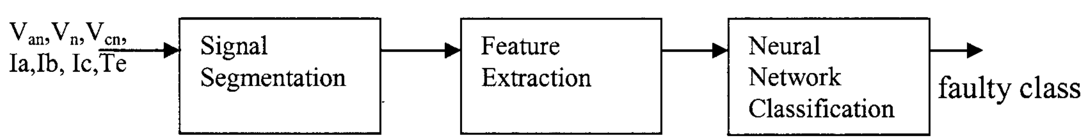


Figure 3. Major computational steps in a signal fault detection system.

2.2 Signal segmentation and feature extraction

Signal fault detection is performed on a segment-by-segment basis. All input signals are segmented using the same fixed sized segments and the two adjacent segments are overlapped in 1/3 of the segment width in order to maintain continuity of information flowing between segments. The basic frequency of the signals is over 80 Hz, and sampling frequency is chosen to be 1000, which is sufficient for this purpose. We chose to use 16 samples in each segment with an overlap of 5 samples between two adjacent segments. A signal of 3000 data samples is segmented into 272 segments. Each signal segment is represented by the following features:

- Max: maximum magnitude of the signal within the segment
- Min: minimum magnitude of the signal within the segment
- Median: median of the signal within the segment
- Mean: mean of the signal within the segment
- Standard deviation: standard deviation of the signal segment
- Zero-frequency component of the power spectrum

The detection of signal faults within a time period requires one segment from each input signal and each segment is represented by the 6 features listed above. Since we have 7 input signals (3 voltage signals, 3 current signals, and 1 torque signal), the combined feature vector to represent a particular state in the electric drive at a particular time is a vector of 42 dimensions. The feature vector is the input to a neural network classifier that determines whether the 7 signals within this time period manifest any fault.

2.3 Smart selections of operation parameters

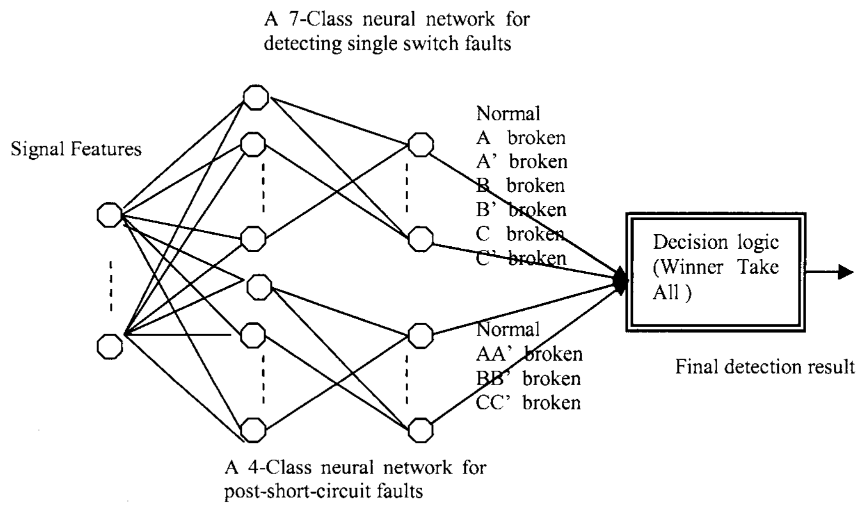
In an electric drive system, the current and voltage signals behave differently under different operation conditions specified by torque and speed. The issue of smart selection of "control parameters" (also referred to as operating point) in the (torque, speed) domain is important for all electric drive diagnostic systems that are trained on simulated data.

A diagnostic system trained on more representative data is more likely to perform better diagnostics in real world system under any operation condition. We developed a machine learning algorithm, CP-Select (**C**ontrol **P**oint-Select), for the generation of training data for a robust electric drive diagnostic system. The CP-Select algorithm automatically selects representative operating points in a given domain of control parameter (CP) space to generate representative training data for a neural network system for fault diagnostics. The operating space for a drive system has two components, i.e. torque (Tq) and speed (Sp). The Tq and Sp pair selected by CP-Select is sent to SIM_drive, which in turn, generates current and voltage signals, I, V, at all three phases at the given speed and torque point under normal and faulty conditions. Diagnostic features are extracted from these signals and feature vectors are used to train an ANN called FDNN, and the performance of the FDNN is evaluated on a validation data set Tv. If the performance is satisfactory, the algorithm stops, otherwise, more operating points are selected.

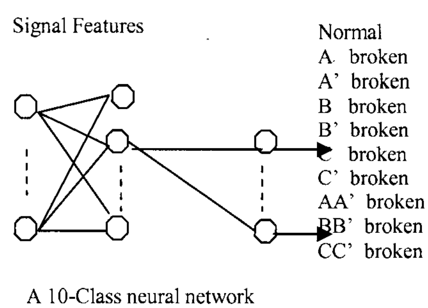
The most complicated component in the CP-Select algorithm is ASCP (Automatic Selection of Control parameters). Initially Φ contains the rectangular space that includes all valid torque and speed points used by a real world electric drive. As the process goes on, Φ contains all subspaces from which potential parameters can be selected. The ASCP algorithm repeatedly removes one parameter space from Φ at a time and performs an iterative process until Φ is empty or the performance of the trained FDNN is satisfactory. At each iteration ASCP selects three sets of points, and each set goes through a simulation, training and evaluation process. The first set of points contains the four corner points and the center point of the current parameter space C_CP and are stored in P_0. The points in P_0 that have not been selected before are sent to SIM_drive to generate new training data. The newly generated training data are combined with the existing ones to form the current training data set, Tr. FDNN is trained on Tr and evaluated on validation data set Tv. If the performance of FDNN on Tv is satisfactory, the process stops. Otherwise it goes on to select the second set of points, which are the interior points of the current parameter space C_CP. The same simulation, training, and evaluation steps are repeated on this set of points. If the performance of FDNN is satisfactory, the process stops. Otherwise the third set of parameters are selected, which contains the four center points on the four sides of C_CP. Again, the same simulation, training and evaluation process is applied to this set of parameters. If the performance of FDNN is satisfactory, the ASCP algorithm stops, otherwise, the current parameter space C_CP is evenly divided into four subspaces CP_1, CP_2, CP_3 and CP_4, which are appended to the parameter space set Φ. All the parameter spaces in Φ are sorted based on the performances of FDNN on the validation points in the space, and the entire process repeats.

2.4. Multi-class Fault Classification using Artificial Neural Networks (ANN)

Neural networks have been successfully applied to a broad range of problems including engineering diagnosis, pattern classification, intelligent manufacturing, control problems and computer vision. Most of the research in neural networks has been in the development of learning and training algorithms for 2-class classifiers, i.e. classifiers with one output node that represent classes 0 and 1. However, fault diagnostics in electric drive has six classes of single switch faults and three classes of post-short-circuit classes. The most common architectures which have been proposed for multi-class neural networks [11], involve a single neural network with K output nodes, where K is the number of faulty classes, and a system of binary neural networks combined with a posterior decision rule to integrate the results of neural networks. A system of binary neural networks requires separate training of each neural network and each trained neural network generates a decision boundary between one class and all others. The most noticeable limitation in this approach is that the decision boundaries generated by the different 2-class neural network classifiers can have overlapped or uncovered regions in the feature space [11]. For the feature vectors that fall on an overlapped region in the feature space, more than one 2-class classifiers can claim the input as their classes, resulting in ambiguity. The feature vectors falling on the regions that are not claimed by any neural networks will be rejected by all neural networks. As a result the resulting system may not generalize well. Another type of multi-class neural network system is to use a single neural network with k output, where $k > 1$. This type of the neural network architecture has the advantage of simple training procedure, and only one neural network is trained for all m classes, where $m > 2$, and, if trained properly a neural network system implemented in this architecture should reduce the ambiguity problem [11].



(a) A system of two neural networks for classifying the single switch and short circuit faults in a 3-phase electric drive



(b) A 10-class single neural network for classifying all 10 classes of faults in a 3-phase electric drive

Figure 4. Two neural network architectures developed for the fault classification in a in an electric drive.

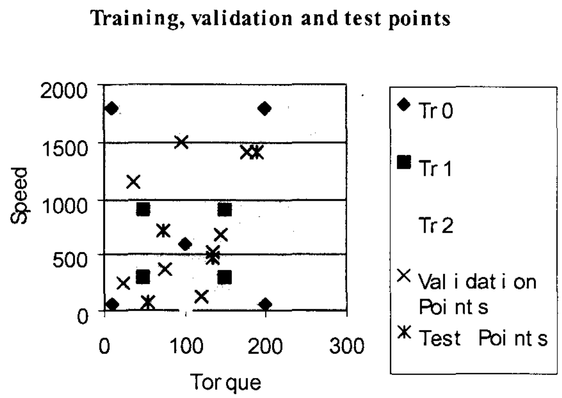
Based on the single neural network architecture, we implemented two different systems of neural networks as illustrated in Figure 4 for the diagnosis of 10 classes of faults in an electric drive: one class represents the normal condition, six classes represent six single switch faults, and the last three classes represent the three post-short-circuit faults. Figure 4 (a) shows a structured diagnostic system consisting of two neural networks, one is trained to classify single switch faults, and the other classifies the post-short-circuit faults, and WTA [11] approach is used to integrate the results from the two neural networks. Figure 4 (b) shows a single neural network trained to classify all 10 classes: normal, six single switch faults, and 3 post-short-circuit faults. One important issue in a multi-class neural network is how to encode the classes in the output nodes of the neural network. In both neural network architectures, we chose to use a "one-hot spot" method described as follows. For a k-class classification problem, we need an output layer of k bits, each class is assigned a unique binary string (codeword) of length k with only 1 bit set to "1" and all other bits are "0." For example if it is a six-class classification problem, class 0 is assigned a codeword of 000001, class 1 is assigned a codeword of 000010, class 2 is assigned of a codeword 000100, etc. The advantage of this encoding is that it gives enough tolerance among different classes. We use the back propagation learning algorithm to train all the neural networks.

In order to evaluate these two neural network systems, we conducted the following experiments using simulated data. The structured multi-class neural network system contains two separately trained neural networks, both having 42 input nodes and 1 hidden layer with 20 hidden nodes. The neural network for single switch fault classification has 7 output nodes, which represent the normal class and the 6 faulty classes. The neural network for the post-short-circuit classification has 4 output nodes, which represent the normal class and the 3 post-short-circuit classes.

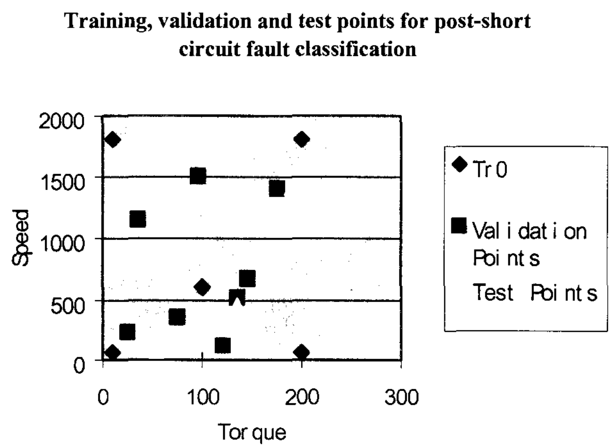
The randomly selected validation and test parameters, and the training parameters generated by the CP-Select algorithm for the six single switch faults are shown in Figure 5 (a) and the parameters for the post-short-circuit are shown in Figure 5 (b). The single-switch fault classification neural network was trained on the control parameters in Tr_0, Tr_1 and Tr_2 generated by the CP-Select algorithm using 3 iterations as described in section 3.2. The post-short-circuit fault classification neural network was trained on the control parameters in Tr_0 shown in Figure 5 (a), which gave 100% correct performance on the validation data shown in the squared points. Therefore the CP-Select algorithm stopped at the end of the first iteration. The four randomly selected test points are shown in triangular in Figure 5(a).

For the 10-class single neural network system, the CP-Select algorithm generated the training points in four iterations resulting in Tr_0, Tr_1, Tr_2 and Tr_3, which are shown in Figure 6 along with the validation points and test points. The 10-class neural network has 42 input nodes and 1 hidden layer with 20 hidden nodes, and 10 output nodes, where one node represents the normal class, and 6 represent the single switch fault classes, and 3 represent the three post-short-circuit faulty classes. It is trained on the data generated by the SIM_drive using the operating points in $Tr_0 \cup Tr_1 \cup Tr_2 \cup Tr_3$.

The test data for both diagnostic systems were the signals generated by SIM_drive from the same four randomly selected (torque, speed) points. 11320 feature vectors were extracted from these signals among which 6792 data samples contain the six single switch faults, and 3396 contain the three post-short-circuit faults, and 1132 are normal. The performances of these two diagnostic systems on the test data set are shown in Figure 6. The structured diagnostic system correctly detected and located all 9 faulty classes and the normal class with 100% correct detection. The single neural network system correctly detected with 100% all the 6 single switch faults, but detected correctly with only 90% and 92% on test data from the post-short-circuit faulty class 1 and class 2.



(a) Randomly selected test and validation set, and the train data selected by CP-Select algorithm for classifying single switch faults



(b) Randomly selected test and validation parameters, and the training parameters selected by the CP-Select for classifying post-short-circuit faults.

Figure 5. Randomly selected test and validation parameters, and the training parameters selected by the CP-Select for classifying single switch faults and post-short-circuit faults.

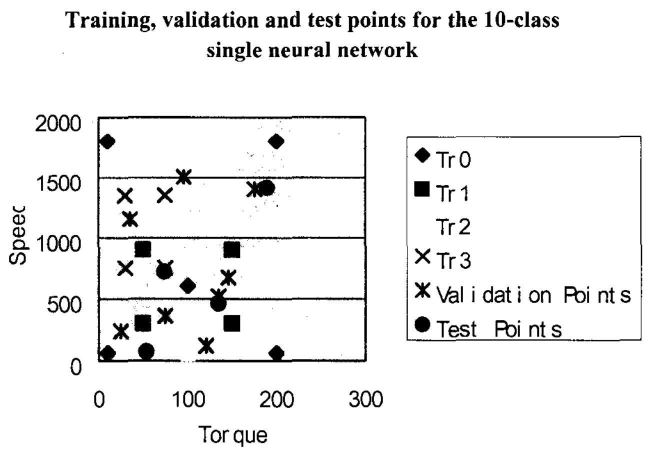


Figure 6. Randomly selected test and validation parameters, and the training parameters selected by the CP-Select using a single neural network classification system.

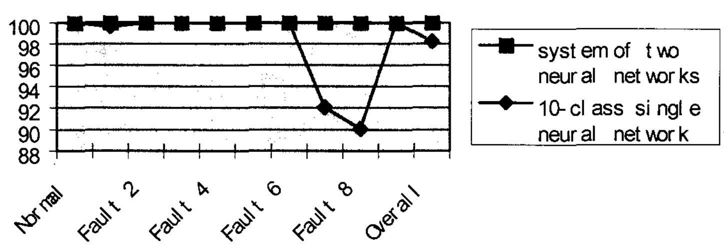


Figure 7: Performances of two different neural network systems

3. Summary and Conclusions

We have presented a diagnostic system driven by a machine learning algorithm for multi-class fault detection in an electric drive system with a three phase induction motor. We presented the machine learning algorithm for the smart selection of vehicle operating points from the (torque, speed) space for the use by the simulated model, SIM_drive, to generate representative training data, and a neural network classification system developed and trained on the signals generated at the representative operation conditions for the fault diagnostics of electric drive inverters.

The intelligent diagnostic system trained with machine learning technology has been evaluated by experimental data. We used the test signals generated by the SIM_drive that contain normal and 9 faulty classes. The results show that the proposed intelligent diagnostics approach is very effective in detecting multiple classes of faults in an electric drive inverter. The authors also investigated two different neural network architectures, a structured neural network system and a single neural network. Our finding is that the structured neural network system gives more accurate diagnostics on all 10 classes than the single neural network system.

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